Louisiana State University
LSU Digital Commons

Faculty Publications | Department of Chemistry

11-1-2019

Detection of chalk in single kernels of long-grain milled rice using imaging and visible/near-infrared instruments

Christopher K. Addison
Louisiana State Univ, Baton Rouge

Follow this and additional works at: https://digitalcommons.lsu.edu/chemistry_pubs

Part of the Chemistry Commons

Recommended Citation

Addison, Christopher K., "Detection of chalk in single kernels of long-grain milled rice using imaging and visible/near-infrared instruments" (2019). *Faculty Publications*. 47.
https://digitalcommons.lsu.edu/chemistry_pubs/47

This Article is brought to you for free and open access by the Department of Chemistry at LSU Digital Commons. It has been accepted for inclusion in Faculty Publications by an authorized administrator of LSU Digital Commons. For more information, please contact gcoste1@lsu.edu.

Received: 17 April 2019 | Revised: 3 September 2019 | Accepted: 8 September 2019

DOI: 10.1002/cche.10220

RESEARCH ARTICLE

Detection of chalk in single kernels of long-grain milled rice using imaging and visible/near-infrared instruments

Paul R. Armstrong[1] | **Anna M. McClung**[2] | **Elizabeth B. Maghirang**[1] | **Ming H. Chen**[2] | **Daniel L. Brabec**[1] | **Kevin F. Yaptenco**[3] | **Adam N. Famoso**[4] | **Christopher K. Addison**[4]

[1]Center for Grain and Animal Health Research, USDA-ARS, Manhattan, KS, USA

[2]Dale Bumpers National Rice Research Center, USDA-ARS, Stuttgart, AR, USA

[3]University of the Philippines Los Banos, Laguna, Philippines

[4]Louisiana State University, Baton Rouge, LA, USA

Correspondence
Paul R. Armstrong, Center for Grain and Animal Health Research, USDA-ARS, Manhattan, KS, USA.
Email: paul.armstrong@ars.usda.gov

Abstract

Background and objectives: To maintain the competitiveness of U.S. long-grain rice in U.S. and foreign markets, having translucent whole milled grain is critical. An objective technique to detect grain chalk, opaque areas in the grain, will provide breeders and industry with an effective tool for developing low-chalk varieties or agronomic practices that reduce chalk occurrence. Two instruments developed at the Center for Grain and Animal Health Research, U.S. Department of Agriculture-Agricultural Research Service (USDA-ARS), a single-kernel near-infrared (SKNIR) tube instrument and a silicon-based light-emitting diode (SiLED) high-speed sorter, were compared with two commercially available imaging instruments, WinSEEDLE and SeedCount used for chalk quantification. Three 2-way chalk classifications were defined for single kernels based on visual inspection: (a) <50% or ≥50% opacity or chalk (modified Grain Inspection, Packers & Stockyards Administration [GIPSA]), (b) <10% or ≥10% opacity (10% cutoff), and (c) 100% opacity or 100% translucent (MaxLevel).

Findings: The SKNIR method provided the best classification for the modified GIPSA definition with an 82.4% average correct classification (CC), that is, 89% and 76% for nonchalky and chalky kernels, respectively. The WinSEEDLE had the best classification for the 10% cutoff definition, with an 84% CC for nonchalky kernels and a 96% CC for chalky kernels. For the MaxLevel definition, average CCs of both the SKNIR and SiLED methods were similar, at 93% and 95%, respectively. The average CCs were lower for both the WinSEEDLE method and the SeedCount method at 14% and 58%, respectively. These low CC values are a result of using a threshold of 100% for chalky or nonchalky kernels, where a single misclassified pixel within the image will cause misclassification. Calibration models developed for both the SKNIR and SiLED methods indicate that their classifications were based mainly on spectral differences near the adsorption bands for starch, protein, and water content.

Conclusions: All of the instruments can be used to classify chalk, but their level of accuracy depends on how chalk is defined.

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
© 2019 The Authors. *Cereal Chemistry* published by Wiley Periodicals, Inc. on behalf of Cereals & Grains Association. This article has been contributed to by US Government employees and their work is in the public domain in the USA.

Significance and novelty: The SiLED has the capability to process seeds at a high rate, and the SKNIR has the potential to measure compositional traits in addition to chalk measurements.

KEYWORDS

imaging, near-infrared-spectroscopy, rice chalk

1 | INTRODUCTION

The occurrence of rice chalk, an opaque area in a rice grain, is a major concern in rice-producing areas worldwide, as it negatively affects yield, appearance, milling, cooking, and palatability qualities. Rice chalk is a visually observed characteristic that consumers and grain processors generally perceive as showing that the rice is of lower quality, which results in market rejection or a substantial price reduction of the rice (Bonifacio & Duff, 1992; Fitzgerald & Resurreccion, 2009). This is in addition to a reduced harvest yield and decreased milled rice recovery (Bautista, Siebenmorgen, & Counce, 2009; Xie et al., 2013; Zhao & Fitzgerald, 2013). Zhao and Fitzgerald (2013) showed that an ~1% decrease in chalkiness resulted in an ~1% increase in head rice yield, which illustrates that rice chalk affects both the quantity and quality of marketable grains.

The U.S. long-grain rice industry has recently faced increased grain chalk in its widely grown cultivars, which has created challenges for the United States to compete in domestic and international markets (McClung, 2013). Poorly packed crystalline regions due to an incomplete accumulation of starch and protein have been attributed to rice chalk (Lin et al., 2016), which manifests as an opaque area in either the entire grain or a portion of the grain. Rice chalk is affected by both genetics and the growing environment. One of the primary goals in rice improvement programs worldwide has been breeding chalkiness out of rice. The growing environment significantly influences the formation of rice chalk (Qiao et al., 2011; Tashiro & Wardlaw, 1991). Tashiro and Wardlaw (1991) found that damage to kernels due to day and night high temperature ranges resulted in (a) white-core kernels when day/night temperatures were 27/22°C, (b) white-backed kernels at both 30/25°C and 33/28°C, (c) milky-white kernels at 36/31°C, and (d) opaque kernels at 39/34°C. Fitzgerald and Resurreccion (2009) also showed that rice chalk increased with high temperature. They reported that from two rice varieties that were studied, the yield of marketable rice was zero for the IR8 variety and about 60% for the IR60 variety, as high-temperature treatments resulted in increased chalk. The relatively slow progress in breeding for low chalkiness reflects the complexity of the underlying mechanisms for how rice chalk occurs and how rice interacts with the growing environment (Lin et al., 2016; Liu et al., 2010).

The ability to detect the presence of chalk in individual rice kernels is important in the rice trade, rice processing, and rice breeding programs. Since rice chalk is a visible characteristic, visual inspection has been the process that has been used for many years. The definition of a rice kernel's chalkiness depends on the objective for which the chalkiness determination is being done. For U.S. rice trading, the standard rice visual reference library used by the USDA-Grain Inspection, Packers & Stockyards Administration (GIPSA) Federal Grain Inspection Service (FGIS) defines chalky rice kernels as whole or broken kernels, which in their cross section contain an opaque white or "chalk-like" area that encompasses 50% or more of the exposed portion (GIPSA, 2016). The percentage of chalky kernels in a milled rice lot has a more stringent maximum limit in long-grain rice compared to either medium- or short-grain rice (GIPSA (Grain Inspection, Packers, and Stockyards Administration) 2009). Long-grain milled rice has a maximum chalky kernel limit of 1% for U.S. No. 1 grade rice, while the same grade of medium- and short-grain rice has a maximum limit of 2%. U.S. No. 4 grade rice allows for 6% chalk in long-grain rice and 8% chalk in medium- and short-grain rice. The limits follow similar patterns for the lower grades of rice, U.S. Grade No. 5, 6, and Sample grade. The Standard Evaluation System (SES) for measuring rice chalkiness, developed by the International Rice Research Institute (IRRI), also involves a visual assessment of the percent area of chalkiness using the following SES scale: (a) no chalk in kernel = Scale 0 or none, (b) <10% chalk in kernel = Scale 1 or small, (c) 10%–20% chalk in kernel = Scale 5 or medium, and (d) >20% chalk in kernel = Scale 9 or large chalk (Gummert, 2010; Juliano, 1985). To date, the visual examination of individual rice kernels for chalk by trained personnel continues to be used by GIPSA and the IRRI.

Two commercially available imaging instruments (WinSEEDLE and Seed Count) that are capable of quantifying rice chalk were evaluated by Grigg and Siebenmorgen (2014). They reported that the WinSEEDLE (Regent Instruments Inc.) and SeedCount (Next Instrument Pty Ltd) instruments closely approximated mass percentage chalkiness results of the FGIS (GIPSA) method for medium grain rice, that is, 1.4%, 1.6%, and 2.2% for GIPSA, WinSEEDLE, and SeedCount methods, respectively. Their long-grain rice, with a low amount of chalky kernels, was also similar to the mass percentage chalkiness approximation of the FGIS method, with chalkiness reported as 0.4%, 0.8%, and 1.1%

for FGIS, WinSEEDLE, and SeedCount methods, respectively. However, their long-grain rice with a high amount of chalkiness showed substantial difference among the methods with 1.4%, 11.7%, and 7.9% for FGIS, WinSEEDLE, and SeedCount, respectively. The authors attributed the difference with the FGIS score being due to greater surface chalkiness of rice kernels. They reported that for both imaging instruments, the number of kernels with chalkiness exceeding 50% closely approximated the chalkiness score of the FGIS method. Other commercial imaging systems that are used or can be modified for measuring rice chalk are the Image Rice Scanner and Image Research Software Platform (Selgron), the JSE-II Rice Chalkiness Visualizer (Daji Photoelectric Instrument Co., Ltd.), the RN300 Rice Quality Analyzer (Kett US), the RN850 Chalky Rice Grain Predictor (Kett Ltd.), the Satake RSQ\10A Grain Scanner (Satake), the Scanner and Rice/Grain Analyzer Software 6980 (Osaw Industrial Products Pvt., Ltd.), the Statistic Analyzer S21 (LKL Technologia; Agromay Soluciones Tecnicas Sl.), and the SC-K rice grain appearance quality image analysis system (Washeng Engineering Co.). With the exception of the Image Rice Scanner, where three-dimensional images of single kernels are obtained in free fall, the other instruments obtain images of kernels that are randomly spread or placed in wells in sample trays on a flatbed scanner. There are also several other commercial image analysis software programs available, for example, ImageJ and GrainScan (Abramoff, Magalhães, & Ram, 2004; Whan et al., 2014). Improved image processing methods have improved the measurement of rice chalk (Guangrong, 2011; Marschalek et al., 2017; Sun, Liu, et al., 2014; Xiaopeng & Yong, 2011; Yoshioka, Iwata, Tabata, Ninomiya, & Ohsawa, 2007).

It is evident from past research and the commercially available rice chalk measurement technologies that imaging has been the focus of research and development efforts in rice chalk detection. While chalk is a visible characteristic, it has been shown that the chemical compositions of translucent and opaque, or chalky, rice kernels are different (Cheng, Zhong, Wang, & Zhang, 2005; Chun, Song, Kim, & Lee, 2009; Lin et al., 2016; Lisle, Martin, & Fitzgerald, 2000). The difference in packing of starch granules in translucent and chalky kernels within the grain can cause differences in light adsorption (Ashida, Iida, & Yasui, 2009). Based on these properties, near-infrared (NIR) spectroscopy may be a potential tool for measuring rice chalk. Two studies have looked at the use of NIR spectroscopy for the measurement of rice chalk, both of which used bulk rice samples. Delwiche, McKenzie, and Webb (1996) used the NIRSystems 6500 visible/NIR scanning monochromator (400–2,498 nm) for two sample set sizes (~100 and ~8 g), which were loaded into appropriate-size sample cells to determine the transparency of the bulk milled rice (SEP = 0.15% transmittance; R^2 = .93). Sun, Yu, Duan, and Zhu (2014) used the Perten DA7200 diode array NIR analyzer (950–1,650 nm) for 40 g bulk rice samples (SEP = 12.1, 3.29, and 0.026; R^2 = .73, .73, and .83 for percent chalky grains, degree of chalkiness, and transparency, respectively). The USDA-ARS, located in Manhattan, Kansas, developed instruments that have been used to determine grain quality characteristics: the single-kernel near-infrared (SKNIR) tube instrument (Armstrong, 2006) and the silicon-based light-emitting diode (SiLED) high-speed sorter (Pearson, Maghirang, & Dowell, 2013). The latter was commercialized by National Manufacturing, Lincoln, Nebraska. These instruments are capable of single-kernel analysis, making them ideal for applications that benefit from automated, nondestructive measurements and the sorting of single grains based on visible and compositional measurements.

The objectives of this study were to compare the effectiveness of measuring rice chalk by two instruments developed by the USDA-ARS (SKNIR and SiLED), both of which are based on spectral measurements in the visible and NIR regions. Two commercially available imaging instruments (WinSEEDLE and SeedCount) were also evaluated using the same sample sets.

2 | MATERIALS AND METHODS

2.1 | Rice samples

Seventy milled rice samples were obtained from 224 long-grain milled rice samples collected by the Dale Bumpers National Rice Research Center, Agricultural Research Service, U.S. Department of Agriculture, Stuttgart, AR, as part of a larger study on rice marketability and competitiveness for the USA Rice Federation (McClung, 2013). The 224 samples consisted of 15 southern US inbred cultivars (Antonio, Bowman, CL111, CL142-AR, CL151, CL152, CL162, Cocodrie, Colorado, Francis, Presidio, Rex, Roy J, Taggart, and Wells) and three hybrids (XL723, XL729, and XL745) grown at six mid-south locations (Beaumont, TX; Crowley, LA; Essex, MO; Harrisburg, AR; Stoneville, MS; and Stuttgart, AR) and one long-grain rice (L206) produced in Biggs, CA. Each location had two planting dates, optimum and delayed. Two milled long-grain rice samples were imported from Thailand and Uruguay. All of the U.S. rice samples were milled in the same rice milling facility to a consistent milling degree based on NIR assessment. From these 224 milled rice samples, a subset of 70 representative samples of the different varieties, growing locations, and planting dates was chosen for this study.

Visual inspections of individual kernels from the 70 samples were done using a 2.75 times magnification OptiVISOR #7 (Donegan Optical Co., Lenexa, KS, USA) to obtain at least 15 rice kernels for each of the six chalk categories, where all kernels were (a) 100% nonchalky, (b) 100% chalky, (c) ≤10% nonchalky, (d) >10% chalky, (e) <50% nonchalky, and (f) ≥50% chalky, for a total of 6,300 kernels. The selected kernels were stored in labeled and sealed glass vials (420 vials

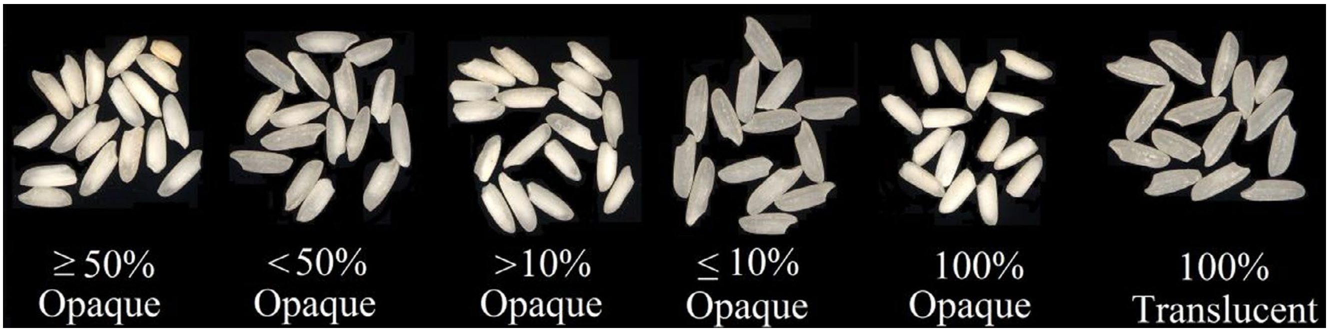

FIGURE 1 Images of visually sorted rice kernels based on the definitions of modified Grain Inspection, Packers & Stockyards Administration (≥50% and <50% opaque), 10% cutoff (>10% and ≤10% opaque), and MaxLevel (100% opaque and 100% translucent) for rice chalk classification [Color figure can be viewed at wileyonlinelibrary.com]

of 15 kernels each). Representative samples of rice chalk categories are shown in Figure 1.

These six chalk categories were used for the three chalk classification definitions: (a) modified GIPSA, which classifies kernels as being either <50% opaque (nonchalky) or ≥50% opaque (chalky); (b) 10% cutoff, which classifies kernels as being either ≤10% opaque (nonchalky) or >10% opaque (chalky); and (c) MaxLevel, which only uses kernels that are either 100% opaque or 100% translucent with no intermediate levels. The 50% cutoff that is used for the modified GIPSA classification is based on the official definition by GIPSA (2016) for chalky kernels as whole or broken rice kernels, which, in cross section, contain an opaque white or "chalk-like" area that encompasses 50% or more of the exposed portion. This study's assessment of kernel chalk was based only on nondestructive visual inspection, and it did not include the destructive cross-sectional test that is officially used by GIPSA in order for the kernels to remain intact for further analysis. Selected chalky kernels were sent to GIPSA for verification of chalkiness using the GIPSA official (destructive) grading system. The MaxLevel definition was included to provide an indication of how well the visible/NIR instruments can distinguish between extreme levels of chalk (100% chalky and 100% nonchalky).

2.2 | Instrumentation, data collection, and analysis

2.2.1 | USDA-ARS tube SKNIR

The tube SKNIR instrument, developed at the USDA-ARS, Stored Product Insect and Engineering Research Unit (SPIERU), Center for Grain and Animal Health Research Center (CGAHR), Manhattan, KS, was used to collect spectral data of single rice kernels (905–1,686 nm). A detailed description of this instrument is provided by Armstrong (2006). An automated prototype has shown that the SKNIR is capable of scanning about three kernels per second and has the potential to measure compositional traits (Armstrong, 2014), but it is expensive to build and maintain. The spectral data of the 6,300 kernels (70 samples × 6 chalk categories × 15 kernels/chalk category) were obtained by dropping each seed, one at a time, into the instrument opening and allowing it to slide down a glass illumination tube, which triggered individual spectral collection. For samples where there were <15 kernels available for each category, randomly picked kernels from that category were rescanned as needed. Of the 70 samples, 50 were used to develop a discriminant prediction model, while the remaining 20 samples were used as validation test samples. There were 750 chalky and 750 nonchalky kernels used to develop the prediction models for each of the three classification definitions, modified GIPSA, 10% cutoff, and MaxLevel. The prediction models for each of the classifications were developed using the multivariate analysis method, linear discriminant analysis (LDA) NCSS 2007 software (version 07.1.19; NCSS). Stepwise variable selection with a significance level of 0.05 was used. Spectral wavelengths were limited to 950–1,636 nm due to spectral noise at the ends, and a standard normal variate (SNV) preprocessing was applied. The software provides classification accuracy of the reference samples from the prediction model, as well as regression coefficients and their associated model wavelengths. The chalk classifications of the validation samples were predicted using the selected calibration models.

2.2.2 | USDA-ARS SiLED high-speed sorter

Pearson et al. (2013) provide a detailed description of the SiLED high-speed sorter developed at the USDA-ARS, SPIERU, CGAHR, Manhattan, KS, which was commercially available through late 2018 by National Manufacturing. The SiLED can process about 20–30 kernels per second and has a simple method for calibration. The instrument is equipped with nine sequentially pulsed LEDs of different wavelengths (470, 527, 624, 850, 880, 910, 940, 970, and 1,070 nm), and it measures the amount of reflected light from a single kernel at each wavelength as it passes the sensor in a free fall. The LED pulse control, digitizing of the photodiode analog signal,

signal processing, and classification are all accomplished using a microcontroller. Two-way sorting is achieved using a solenoid-activated air nozzle. The same set of kernels used in the SKNIR instrument tests was used for the SiLED high-speed sorter tests. Since the SiLED performs a two-way classification and the calibration is limited to scanning 200 kernels from each classification, only 20 samples with 10 kernels per sample were used to develop the discriminate models (200 chalky and 200 nonchalky kernels) for each of the three chalk classification definitions. The remaining 50 samples (15 kernels/sample for each of the two classifications) were then used as validation test samples ($n = 1{,}500$ kernels). During the sorting tests, the 15 kernels for each category were run through the instrument independently to prevent mixing classifications. The number of kernels sorted into each classification was recorded.

TABLE 1 Wavelengths used by the SKNIR instrument in the discriminant analysis function of the different chalk definitions

Chalk definition	Wavelengths, nm[a]
modified GIPSA <50% or ≥50% opaque	1,154, 1,253, 1,269, 1,280, 1,335, 1,376, 1,414, 1,470, 1,477, 1,525, 1,551, 1,554, 1,607, 1,644
10% cutoff ≤10% or >10% opaque	905, 1,083, 1,139 1,162, 1,194, 1,280, 1,332, 1,406, 1,596, 1,631
MaxLevel 100% Trans−100% opaque	1,218, 1,239, 1,246, 1,269, 1,278, 1,282, 1,299, 1,312, 1,329, 1,391, 1,400, 1,581, 1,607, 1,617, 1,630, 1,686

Abbreviations: GIPSA, Grain Inspection, Packers & Stockyards Administration; SKNIR, single-kernel near-infrared.

[a]Determined by stepwise selection during discriminant analysis.

2.2.3 | Imaging instruments: WinSEEDLE Pro and SeedCount

The WinSEEDLE™ Pro (version 2013b; Regent Instruments Canada Inc.) is an image analysis system that uses an optical scanner with special lighting to capture high-resolution images. These images are then processed to discriminate between chalky and nonchalky areas in single kernels, based on the color space of hue, saturation, and intensity, as defined previously by the Dale Bumpers National Rice Research Center. The SeedCount digital imaging system uses a flatbed scanner and associated software to determine the chalkiness of the grains, including the percentage of chalky portions in individual kernels (Next Instruments Pty Ltd.). The SeedCount instrument scans the top of each kernel in the tray. The instrument uses a difference in luminance to determine chalk; however, since it only scans the top surface, the presence of chalk that is not in the viewing area may not be detected. The existing calibrations for chalk determination were used for both of these commercial instruments with the selected threshold levels varied based on the chalk definition being analyzed.

3 | RESULTS AND DISCUSSION

3.1 | Calibration model for the SKNIR instrument

Discriminate models were developed from the spectra using NCSS ver. 7 software; the wavelengths used in the model are shown in Table 1. The selected wavelengths, although they varied across the classification definitions, indicated that the discrimination was partially based on starch, protein, and water adsorption bands. For example, the model wavelengths of 1,581 nm for MaxLevel, 1,551 nm for modified GIPSA, and 1,596 nm in 10% cutoff corresponded to absorption bands for starch including 1,463 nm indicating the discrimination of amylose content (Pandiselvam, Thirupathi, & Vennila, 2016; Shenk, Workman, & Westerhaus, 1992; Williams & Norris, 2001). Similarly, the model wavelengths of 1,630 nm for MaxLevel, approximately 1,269 and 1,280 nm for modified GIPSA, and approximately 1,202, 1,280, and 1,631 nm for 10% cutoff corresponded to wavelength absorption bands for protein (Pandiselvam, Thirupathi, Mohan, & Uma, 2015; Shenk et al., 1992; Williams & Norris, 2001). All models contained the wavelengths of approximately 1,400–1,415 nm, which are associated with a water absorption band. These results are similar to the findings that starch composition and water absorption index differ between chalky and vitreous kernels (Kim, Lee, Kim, & Kim, 2000; Lin et al., 2016; Lisle et al., 2000; Patindol & Wang, 2003).

3.2 | Calibration model for the SiLED instrument

Similar to the calibration models developed for the tube SKNIR, three calibration models were developed for the SiLED sorter for two-way classification of chalky and nonchalky milled rice using nine wavelengths (470, 527, 624, 850, 880, 910, 940, 970, and 1,070 nm). The discriminant models that were generated by the instrument for calibration (Table 2) showed acceptable levels of correct classification (CC) accuracy across the classification definitions: (a) modified GIPSA, 81.5% for chalky and 87.5% for nonchalky rice kernels; (b) 10% cutoff, 85.0% for chalky and 87.5% for nonchalky; and (c) MaxLevel, 87.5% for chalky and 99.0% for nonchalky.

3.3 | Comparison of rice chalk classifications: Visible/NIR and imaging instruments

Table 3 summarizes the classification accuracies of the four instruments for detecting different chalk definitions. Also shown in Table 3 is the average percentage of chalk in individual rice kernels for each of the imaging instruments.

TABLE 2 Projected classification accuracy of the SiLED high-speed sorter based on a calibration model developed using discriminant analysis

	SiLED chalk prediction model	
Chalk definition	Number of kernels	Projected classification accuracy, %
modified GIPSA		
<50%	200	87.5
≥50% Chalky	200	81.5
10% cutoff		
≤10%	200	87.5
>10% Chalky	200	85.0
MaxLevel		
100% Translucent	200	99.0
100% Chalky	200	87.5

Abbreviations: GIPSA, Grain Inspection, Packers & Stockyards Administration; SiLED, silicon-based light-emitting diode.

3.3.1 | Modified GIPSA chalk definition

For the 50% cutoff that is set for the modified GIPSA chalk definition, which is the cutoff for commercial trade, the SKNIR provided the highest average % correct classification (82.4%) compared to the SiLED (77.6%), SeedCount (74.3%), and WinSEEDLE (66.5%). While the WinSEEDLE provided the highest correct classification for nonchalky kernels (99.2%), it had the lowest correct classification for chalky kernels (33.7%). These classification trends for the two imaging instruments are also reflected in the results obtained for the percent of chalk present in individual rice kernels. The average % chalk in milled rice kernels that were sorted as nonchalky was 12.6% using the WinSEEDLE and 6.7% using the SeedCount. At the GIPSA chalk definition cutoff of 50%, the amount of chalk in these rice kernels was substantially lower and, as such, translated to higher correct classifications. On the other hand, the % chalk of the sorted chalky kernels was found to be 43.4% using the WinSEEDLE and 52.8% using the SeedCount. These averages are only slightly lower than or slightly higher than the 50% GIPSA cutoff, which resulted in a substantial number of kernels being misclassified by the imaging instruments as nonchalky. This prompted further investigation into what may be causing the low correct classification of chalky kernels. Some of the misclassifications can be attributed to the manner of kernel presentation to the instrument. For example, milled rice kernels with chalk may be presented to the instrument on a side where the chalk is not imaged and thus misclassified as nonchalky. Other potential sources of errors were investigated by sending selected samples that were poorly classified to GIPSA—Arkansas for official (destructive) chalk evaluation. Based on the scores provided by GIPSA, another potential source of discrepancy in classification may be the presence of surface chalk on samples, but when the cross sections were viewed, they had a translucent center.

TABLE 3 Percent correct classification (CC) using the four selected instruments for detecting different chalk definitions

	Chalk determination instruments									
	USDA-ARS instruments				Commercial imaging instruments					
	SKNIR		SiLED		WinSEEDLE			SeedCount		
Chalk definition	No. of kernels	% CC	No. of kernels	% CC	No. of kernels	% CC	% Chalk[a] in kernels	No. of kernels	% CC	% Chalk[a] in kernels
modified GIPSA										
<50% Chalky	300	89.0	750	95.5	1,065	99.2	12.6	1,065	97.2	6.7
≥50% Chalky	300	75.7	750	59.7	1,065	33.7	43.4	1,065	51.4	47.1
Average		82.4		77.6		66.5				74.3
10% cutoff										
≤10% Chalky	300	96.7	750	93.7	1,065	84.1	5.4	1,065	90.9	1.7
>10% Chalky	300	68.3	750	62.4	1,065	95.7	38.3	1,065	71.7	36.7
Average		82.5		78.1		89.9				81.3
MaxLevel										
100% Translucent	300	90.3	750	98.5	1,065	28.1	3.0	1,065	96.0	0.6
100% Chalky	300	96.3	750	91.6	1,044	0.0	53.9	1,035	20.4	70.3
Average		93.3		95.1		14.1			58.2	

Abbreviations: GIPSA, Grain Inspection, Packers & Stockyards Administration; SiLED, silicon-based light-emitting diode; SKNIR, single-kernel near-infrared.
[a]Average percent chalk in sample.

3.3.2 | 10% cutoff chalk definition

For the 10% cutoff chalk definition, the WinSEEDLE provided the highest average CC at 89.9% when compared to the other instruments, including the SKNIR (82.5%), SeedCount (81.3%), and SiLED (78.1%). The SKNIR and SiLED had higher CC of nonchalky rice (96.7% and 93.7%, respectively) compared to the other imaging instruments, that is, the WinSEEDLE (84.1%) and SeedCount (90.9%). When the WinSEEDLE (95.7%) and SeedCount (71.7%) were compared to the SKNIR (68.3%) and SiLED (62.4%), both of the imaging instruments had higher CC for chalky kernels. The average chalk measured for the ≤10% chalky seeds for the imaging instruments was 5.4% (WinSEEDLE) and 1.7% (SeedCount), which indicates a good ability to correctly classify this group. There was a substantial difference in classification for the >10% chalky seeds for the WinSEEDLE (95.7% CC) and SeedCount (71.7% CC), even though the average chalk in these groups was similar (38.3% for WinSEEDLE and 36.7% for SeedCount).

3.3.3 | MaxLevel chalk definition

The MaxLevel chalk definition was included for evaluation in this study to determine the discrimination ability at the maximum possible amount of chalk difference of 100% chalk versus 100% nonchalky. While this is not a realistic grading situation, it provides the largest contrast between chalky kernels and a baseline for the best possible performance to be expected for rice that is comprised of a range of chalkiness. The SKNIR and SiLED discriminate models both showed high CCs, with an average of 93.3% for the SKNIR and 95.1% for the SiLED instrument. These results provide an indication of the well-known phenomenon for light to pass through a material and be selectively absorbed. The high classification accuracies reflected how the NIR light penetration was different for chalky and nonchalky rice kernels.

With an average of 14.1% for the WinSEEDLE and 58.2% for the SeedCount, both imaging instruments showed poor classification. The MaxLevel chalk definition is not good for these types of instruments, as each instrument has to determine whether all pixels within the kernel area are either chalky or not. The correct pixel classification is unlikely to occur due to edge effects on the image, slight color differences, or the presence of dust and other particles. This is illustrated by the images from the WinSEEDLE instrument (Figure 2), which show the original kernels and the areas that are defined as chalky (white color) for 100% chalky kernels. As such, any kernel that has even a small translucent area will not be classified as 100% chalky, and any kernel having a speck of opaqueness will not be classified as nonchalky. Incorporation of discriminate analysis methods on imaged data could improve classification accuracy, as classifications would be based on the probability of being in a group instead of relying solely on pixel counts.

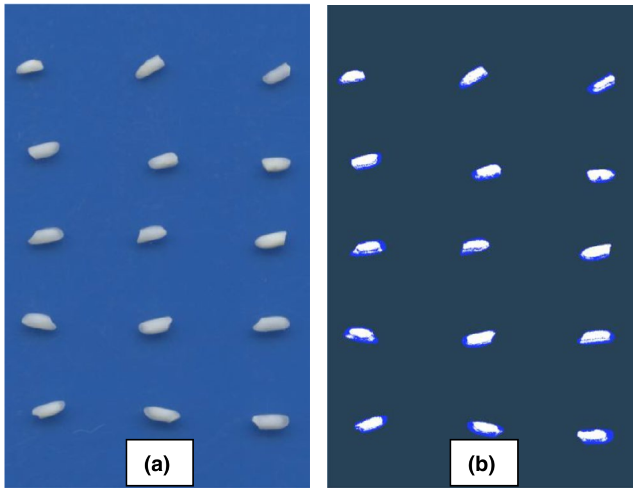

FIGURE 2 Images obtained from the WinSEEDLE instrument showing (a) original and (b) the chalk area (white color) defined by the WinSEEDLE for kernels manually classified as 100% chalky [Color figure can be viewed at wileyonlinelibrary.com]

4 | CONCLUSIONS

Four instruments (the SKNIR, SiLED, WinSEEDLE, and SeedCount) were evaluated for their ability to detect chalk, and all four instruments showed good potential for two-way classification of chalky and nonchalky kernels, with varying levels of accuracy depending on the chalk classification definition.

Both the SKNIR and SiLED instrument chalk classifications appear to be partially based on differences in starch, protein, and water content, whereas the other imaging instruments rely on color differences of pixels and pixel areas. Both the WinSEEDLE and SeedCount instruments generally classified chalkiness similar to that of the SKNIR and SiLED, except for the MaxLevel chalk definition, which resulted in low correct classifications. These poor classifications are attributed to a very small percentage of pixels not being classified correctly.

ACKNOWLEDGMENTS

The authors would like to thank the USA Rice Federation for coordinating the study that generated the rice samples used in this project. Contributors included the state rice breeding programs located in Crowley, LA; Beaumont, TX; Stuttgart, AR; and Stoneville, MS, along with RiceTec, Inc., a private rice breeding company. All samples were milled by the Louisiana Rice Mill located in Crowley, LA. We also thank Mayra Perez-Fajardo and GIPSA for their assistance in the visual inspection and sorting of samples for chalk. The mentioning

of a proprietary product or trade name does not constitute a recommendation or endorsement by the US Department of Agriculture. The USDA is an equal opportunity provider and employer.

ORCID

Paul R. Armstrong https://orcid.org/0000-0002-4012-0010
Ming H. Chen https://orcid.org/0000-0002-3449-2504
Adam N. Famoso https://orcid.org/0000-0002-6461-6504

REFERENCES

Abramoff, M. D., Magalhães, P. J., & Ram, S. J. (2004). Image processing with ImageJ. *Biophotonics International*, *11*, 36–42.

Armstrong, P. R. (2006). Rapid single-kernel NIR measurement of grain and oil-seed attributes. *Applied Engineering in Agriculture*, *22*, 767–772. https://doi.org/10.13031/2013.21991

Armstrong, P. R. (2014). Development and evaluation of a near-infrared instrument for single-seed compositional measurement of wheat kernels. *Cereal Chemistry*, *91*, 23–28. https://doi.org/10.1094/CCHEM-07-13-0132-R

Ashida, K., Iida, S., & Yasui, T. (2009). Morphological, physical, and chemical properties of grain and flour from chalky rice mutants. *Cereal Chemistry*, *86*, 225–231. https://doi.org/10.1094/CCHEM-86-2-0225

Bautista, R. C., Siebenmorgen, T. J., & Counce, P. A. (2009). Rice kernel chalkiness and milling quality relationship of selected cultivars. *B. R. Wells Rice Research Studies*, AAES Research Series, *581*, 220–2009.

Bonifacio, E. P., & Duff, B. (1992). The impact of postharvest operations on rough rice and milled rice quality in the Philippines. In L. J. Unnevehr, B. Juliano & B. Duff (Eds.), *Consumer demand for rice grain quality* (pp. 149–157). Manila, Philippines: International Rice Research Institute.

Cheng, F. M., Zhong, L. J., Wang, F., & Zhang, G. P. (2005). Differences in cooking and eating properties between chalky and translucent parts in rice grain. *Food Chemistry*, *90*, 39–46.

Chun, A., Song, J., Kim, K. J., & Lee, H. J. (2009). Quality of head and chalky rice and deterioration of eating quality by chalky rice. *Journal of Crop Science and Biotechnology*, *12*, 239–244. https://doi.org/10.1007/s12892-009-0142-4

Delwiche, S. R., McKenzie, K. S., & Webb, B. D. (1996). Quality characteristics in rice by near-infrared reflectance analysis of whole-grain milled samples. *Cereal Chemistry*, *73*, 257–263.

Fitzgerald, M. A., & Resurreccion, A. P. (2009). Maintaining the yield of edible rice in a warming world. *Functional Plant Biology*, *36*, 1037–1045. https://doi.org/10.1071/FP09055

GIPSA (Grain Inspection, Packers & Stockyards Administration) (2009). *United States standards for rice*. Washington, DC: Federal Grain Inspection Service, U.S. Department of Agriculture.

GIPSA (2016). *Visual reference library – Rice*. Washington, DC: Federal Grain Inspection Service, U.S. Department of Agriculture.

Grigg, B. C., & Siebenmorgen, T. J. (2014). A comparison of methods used to quantify chalkiness of head rice. In R. J. Norman & K. A. K. Moldenhauer (Eds.), *B. R. Wells Arkansas rice research studies 2014* (pp. 314–320). AAES Research Series 626. Fayetteville, AR: Arkansas Agricultural Experiment Station (AAES).

Guangrong, L. (2011). *Detection of chalk degree of rice based on image processing technique* (pp. 515–518). 2011 International Conference on Intelligence Science and Information Engineering

Gummert, M. (2010). *Measuring white rice quality. Rice Knowledge Bank, Training Fact Sheets*. Los Banos, Laguna, Philippines: International Rice Research Institute.

Juliano, B. O. (1985). Criteria and tests for rice grain qualities. In B. O. Juliano (Ed.), *Rice: Chemistry and technology* (pp. 443–524). St. Paul, MN: American Association of Cereal Chemists Inc.

Kim, S. S., Lee, S. E., Kim, O. W., & Kim, D. C. (2000). Physicochemical characteristics of chalky kernels and their effects on sensory quality of cooked rice. *Cereal Chemistry*, *77*, 376–379. https://doi.org/10.1094/CCHEM.2000.77.3.376

Lin, Z., Zheng, D., Zhang, X., Wang, Z., Lei, J., Liu, Z., … Ding, Y. (2016). Chalky part differs in chemical composition from translucent part of japonica rice grains as revealed by a notched-belly mutant with white-belly. *Journal of the Science of Food and Agriculture*, *96*, 3937–3943. https://doi.org/10.1002/jsfa.7793

Lisle, A. J., Martin, M., & Fitzgerald, M. A. (2000). Chalky and translucent rice grains differ in starch composition and structure and cooking properties. *Cereal Chemistry*, *77*, 627–632. https://doi.org/10.1094/CCHEM.2000.77.5.627

Liu, X., Guo, T., Wan, X., Wang, H., Zhu, M., Li, A., … Wan, J. (2010). Transcriptome analysis of grain-filling caryopses reveals involvement of multiple regulatory pathways in chalky grain formation in rice. *BMC Genomics*, *11*, 730. https://doi.org/10.1186/1471-2164-11-730

Marschalek, R., Silva, M. C., dos Santos, S. B., Manke, J. R., Bieging, C., Porto, G., … de Andrade, A. (2017). Image – Rice grain scanner: A three-dimensional fully automated assessment of grain size and quality traits. *Crop Breeding & Applied Biotechnology*, *17*, 89–97. https://doi.org/10.1590/1984-70332017v17n1s15

McClung, A. (2013). *Quality assessment of rice samples produced in 2012* (p. 9). Report to the U.S. Rice Federation Rice Marketability and Competitiveness Task Force. Stuttgart, AR.

Pandiselvam, R., Thirupathi, V., Mohan, S., & Uma, D. (2015). Development of PLS model for rapid estimation of protein content of rice using fourier transform near infrared spectroscopy. *Agricultural Engineering*, *4*, 27–34.

Pandiselvam, R., Thirupathi, V., & Vennila, P. (2016). Fourier transform – Near infrared spectroscopy for rapid and nondestructive measurement of amylose content of paddy. *Agricultural Engineering*, *2*, 93–100.

Patindol, J., & Wang, Y. J. (2003). Fines structures and physicochemical properties of starches from chalky and translucent rice kernels. *Journal of Agricultural Food Chemistry*, *51*, 2777–2784.

Pearson, T. C., Maghirang, E. B., & Dowell, F. E. (2013). A multispectral sorting device for wheat kernels. *Journal of Agricultural Science and Technology*, *2*, 45–60. https://doi.org/10.7726/ajast.2013.1004

Qiao, J., Liu, Z., Deng, S., Ning, H., Yang, X., Lin, Z., … Ding, Y. (2011). Occurrence of perfect and imperfect grains of six japonica rice cultivars as affected by nitrogen fertilization. *Plant and Soil*, *349*, 191–202. https://doi.org/10.1007/s11104-011-0861-4

Shenk, J. S., Workman Jr, J. J., & Westerhaus, M. O. (1992). Application of NIR spectroscopy to agricultural products. In D. A. Burns & E.

W. Ciurczak (Eds.), *Handbook of near-infrared analysis* (pp. 383–431). New York, NY: Marcel Dekker Inc.

Sun, C., Liu, T., Ji, C., Jiang, M., Tian, T., Guo, D., … Liang, X. (2014). Evaluation and analysis the chalkiness of connected rice kernels based on image processing technology and support vector machine. *Journal of Cereal Science*, *60*, 426–432. https://doi.org/10.1016/j.jcs.2014.04.009

Sun, C., Yu, Y., Duan, B., & Zhu, Z. (2014). Rapid prediction of rice quality characteristics by near-infrared reflectance spectroscopy for breeding programs. *Cereal Chemistry*, *91*, 270–275. https://doi.org/10.1094/CCHEM-08-13-0164-R

Tashiro, T., & Wardlaw, I. F. (1991). The effect of high temperature on kernel dimensions and the type and occurrence of kernel damage in rice. *Australian Journal of Agricultural Research*, *42*, 486–496. https://doi.org/10.1071/AR9910485

Whan, A. P., Smith, A. B., Cavanagh, C. R., Ral, J.-P.-F., Shaw, L. M., Howitt, C. A., & Bischof, L. (2014). GrainScan: A low cost, fast method for grain size and colour measurements. *Plant Methods*, *10*, 23. https://doi.org/10.1186/1746-4811-10-23

Williams, P. C., & Norris, K. (2001). *Near-infrared technology in the agricultural and food industries* (2nd ed.). St. Paul, MN: American Association of Cereal Chemists Inc.

Xiaopeng, D., & Yong, L. (2011). *Research on the rice chalkiness measurement based on the image processing technique* (pp. 448–451). 2011 International Conference on Intelligence Science and Information Engineering.

Xie, L., Tang, S., Chen, N., Luo, J., Jiao, G., Shao, G., … Hu, P. (2013). Rice grain morphological characteristics correlate with grain weight and milling quality. *Cereal Chemistry*, *90*, 587–593. https://doi.org/10.1094/CCHEM-03-13-0055-R

Yoshioka, Y., Iwata, H., Tabata, M., Ninomiya, S., & Ohsawa, R. (2007). Chalkiness in rice: Potential for evaluation with image analysis. *Crop Science*, *47*, 2113–2120. https://doi.org/10.2135/cropsci2006.10.0631sc

Zhao, X., & Fitzgerald, M. (2013). Climate change: Implications for the yield of edible rice. *PLoS One*, *8*(6), e66218.

How to cite this article: Armstrong PR, McClung AM, Maghirang EB, et al. Detection of chalk in single kernels of long-grain milled rice using imaging and visible/near-infrared instruments. *Cereal Chem*. 2019;96:1103–1111. https://doi.org/10.1002/cche.10220